




# The sspm R package: spatial surplus production models for the management of northern shrimp fisheries

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## Statement of need

Population models are important tools for making management decisions, especially in fisheries, where predictive methods like Surplus Productivity Models (SPMs) are widely used. Fisheries analysts and managers often lack user-friendly, flexible tools to implement and apply SPMs. In addition, SPMs are rarely spatially explicit and usually cannot account for relevant ecosystem drivers. Therefore, there is a need for tools that implement spatially explicit surplus production models (SSPMs). The Northern Shrimp stock in the Newfoundland and Labrador Shelves is an example of a stock in need of an SSPM that can integrate important spatially-structured ecosystem drivers.

## Summary

Population modelling is an exercise of interest within environmental sciences and adjacent fields. Early population models such as the logistic model assumed that while the abundance of a population might change over time, the conditions governing parameters affecting that rate of change, such as the maximum rate of growth or the carrying capacity of the population, stay constant over time (Gotelli, 2008). Modern population models increasingly acknowledge the non-stationary nature of wild populations and work to incorporate environmental fluctuations into dynamic models (Thorson et al., 2017, 2015). Population models designed to answer applied resource management questions, such as fisheries stock models, increasingly address how the dynamics of stocks vary across space and time.

Resource managers are becoming increasingly interested in how variation in ecosystem factors such as predator abundance and abiotic variables impact the spatiotemporal variability of population parameters, such as productivity (Szuwalski & Hollowed, 2016; Zhang et al., 2021). Further, treating spatially structured stocks as single unstructured stocks can lead to substantially biased estimates of population change (Thorson et al., 2015). However, stock models that explicitly incorporate spatial dynamics and time-varying ecosystem variables are still rare in fisheries science, despite the push for more ecosystem-based management methods in fisheries management (Berkes, 2012; Crowder et al., 2008; Tam et al., 2017).

Surplus production models (SPMs) are one of the classic models used in fisheries and are based on modelling changes in the total biomass of a stock in a given location over time as a function of current stock abundance and fishing pressure (Walters et al., 2008). Classically, SPMs assume single unstructured stocks with purely logistic dynamics (Walters et al., 2008) and, as such, have been of limited use for modelling more complex stocks. They are useful in

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39 data-poor contexts where the age structure of the population is not accessible or when age  
40 or length structure do not change substantially over time (Prager, 1994; Punt, 2003). SPMs  
41 typically model spatially constant productivity. They also assume that populations are only  
42 affected by past abundance and fishing, which ignores stressors like climate change which  
43 affect growth rates independently of fishing pressure.

44 In the context of global warming and shifting ranges, fisheries productivity is likely to be  
45 a moving target (Karp et al., 2019), and managers need better methods that account for  
46 varying productivity (Szuwalski & Hollowed, 2016). The Northern Shrimp (*Pandalus borealis*)  
47 in the Newfoundland and Labrador Shelves, which has undergone several periods of large-scale  
48 biomass change in the last two decades, despite a relatively constant harvest regime, is a prime  
49 example of a population thought to be affected by environmental conditions (DFO, 2019).  
50 These populations currently lack a population model to understand the drivers of this change  
51 and to predict how fishing pressure and changing environmental conditions may affect future  
52 abundance.

53 Population models like SPMs usually fall under the two following categories: process-based  
54 and statistical models. Process-based models often rely on differential or difference equations  
55 and are based on replicating the underlying processes (e.g., predation, recruitment, dispersal)  
56 driving population dynamics. Statistical models instead fit a regression model to time series  
57 of population abundances, abundance indices, or productivities, with some assumed error  
58 distribution for variation around predictions.

59 We have chosen a statistical approach to fitting SPMs. Statistical models allow for estimation  
60 of parameter uncertainty and ranges of model predictions and for flexibly incorporating potential  
61 ecosystem drivers into models (Plagányi et al., 2014). Statistical models also allow for straight-  
62 forward estimation of spatial variation in population parameters such as maximum productivity  
63 or density dependence from data, in the absence of theory predicting how these parameters  
64 should vary.

65 In this paper, we use a statistical approach to fitting SPMs using Generalized Additive Models  
66 (GAMS), estimated using the mgcv R package (Wood, 2017) as the backend. We apply this  
67 approach to the population of Northern Shrimp of the Newfoundland and Labrador Shelves,  
68 leveraging the smoothing properties of GAMs to account for varying productivity across time  
69 and space. The resulting model is a spatial SPM (SSPM), implemented via an R package:  
70 sspm.

71 While the initial application of this model was modelling Newfoundland and Labrador Northern  
72 Shrimp stocks (Pedersen et al., 2022), the R package sspm is designed to make spatially-explicit  
73 surplus production models (SSPM) easier to estimate and apply to any spatially structured  
74 stock. The package uses GAMs to smooth spatiotemporally varying biomass, and to fit SSPMs  
75 based on changes in fitted biomass, observed catch, and spatially structured environmental  
76 predictors. It includes a range of features to manipulate harvest and biomass data. Those  
77 features are organized in a stepwise workflow, whose implementation is described in more detail  
78 in Figure 1 and in the next section.

79 Although it was developed in a fisheries context, the package is suited to model spatially-  
80 structured population dynamics in general.

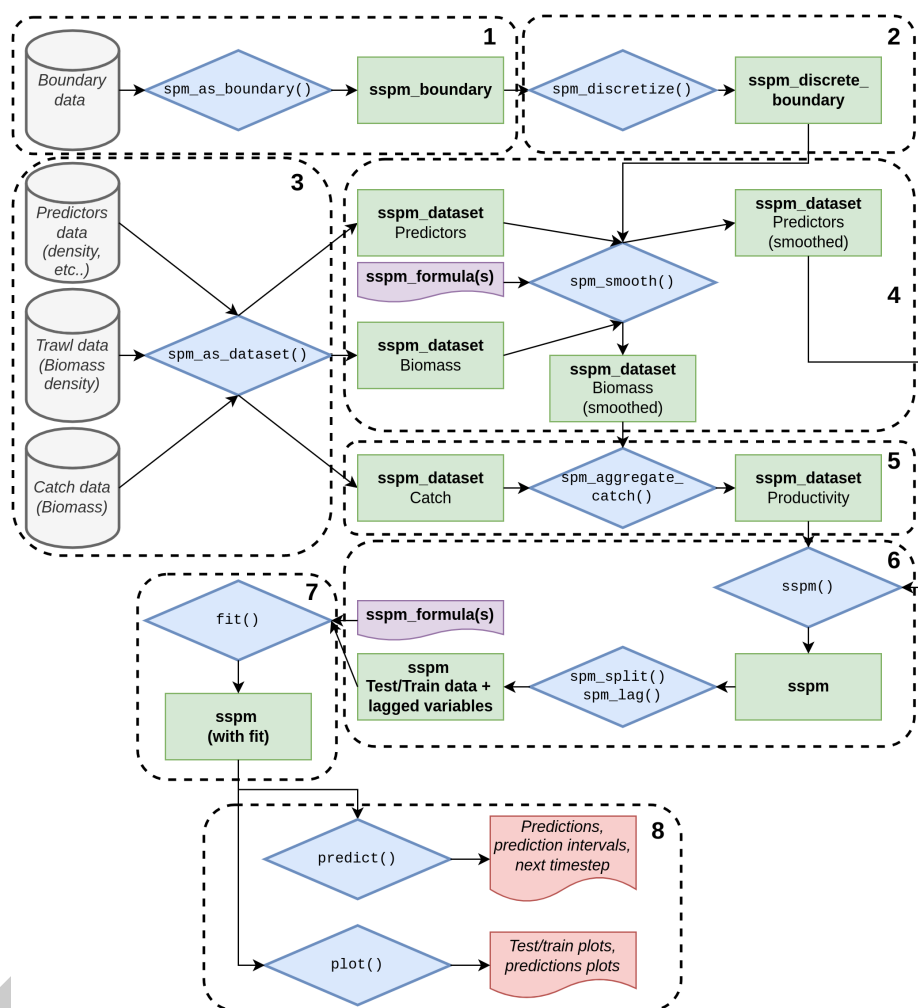
## 81 Package design

82 The package follows an object oriented design, making use of the S4 class systems to model a  
83 stepwise workflow: (Figure 1).

84 The key workflow steps are:

- 85 ■ Discretization and aggregation of spatially structured observations into discrete patches,

86 with a range of methods of discretization (random or custom sampling, Voronoi tessella-  
 87 tion, or Delaunay triangulation).  
 88 1. Provided boundary data in the form of a shapefile is converted into a `sspm_boundary`  
 89 object using `spm_as_boundary()` to define the boundary/region of interest.  
 90 2. The region within the boundary is discretized into patches with the  
 91 `spm_discretize()` function, creating a `sspm_discrete_boundary` object.  
 92 ■ Spatiotemporal smoothing of biomass and environmental predictors using GAMs.  
 93 3. The `spm_as_dataset()` function turns user-provided data frames of raw observa-  
 94 tions into `sspm_dataset` objects that explicitly track locations, data types, and  
 95 aggregation scales for each input. `sspm` recognizes three types of data: **trawl**  
 96 (i.e. biomass estimates from scientific surveys), **predictors**, and **catch** (i.e., harvest).  
 97 4. The `spm_smooth()` function use spatiotemporal GAMs to smooth the biomass and  
 98 predictor data, based on the spatial structure from `sspm_discrete_boundary`. The  
 99 user specifies a GAM formula with custom smooth terms. The output is another  
 100 `sspm_dataset` object with a `smoothed_data` slot which contains the smoothed  
 101 predictions for all patches.  
 102 ■ Computation of surplus productivity based on biomass density and fishing effort.  
 103 5. The `spm_aggregate_catch()` function aggregates catch into patches and years and  
 104 calculates patch-specific productivity for each year as the ratio of estimated biomass  
 105 density plus catch from the next year divided by estimated biomass density of the  
 106 current year. The result is returned as a `sspm_dataset`.  
 107 6. The `sspm()` function combines productivity and predictor datasets into a single  
 108 dataset. Additionally, the user may create lagged versions of predictors with  
 109 `spm_lag()` and split data into testing and training sets for model validation with  
 110 `spm_split()` at this stage.  
 111 ■ Fitting of SSPMs to productivity estimates with GAMs.  
 112 7. The `spm()` function is used to fit a SSPM model to the output of step 6, using a  
 113 GAM model with custom syntax able to model a range of SSPMs. The output is  
 114 an `sspm` object.  
 115 ■ Visualization of results, and one-step-ahead projections of biomass for model validation  
 116 and scenario-based predictions.  
 117 8. Plots can be generated with the `plot()` method. Predictions from the fitted model  
 118 can be obtained using the built-in `predict()` method, including confidence and  
 119 prediction intervals



**Figure 1:** The sspm workflow. Gray cylinders represent raw, unprocessed sources of data. Each blue diamond shape represents a function processing a raw input and validating it, or producing an intermediate package object, represented as a green object. Secondary objects like formulas, which must be created by the user, are represented by a purple document shape. Finally, outputs are represented by a red document shape. The steps of the workflow as described above are denoted by dotted lines and corresponding step number.

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